

(In)equality in Education and Economic Development

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Abstract

This paper investigates the relationship between economic development and the average level of education as well as the degree of inequality in the distribution of education, respectively. Approaching this question in a dynamic panel over 60 years and 143 countries with a system GMM estimator reveals strong support for the inclusion of an interaction term between the education Gini coefficient and average years of schooling, indicating the existence of nonlinear effects. We contribute to the literature in providing strong evidence that more schooling is good for economic growth - irrespective of its distribution - but that the coefficient is variable and substantially declining in inequality. On the other hand, inequality is positively related to economic growth for low average levels of education, whereas highly educated countries exhibit a statistically insignificant negative relationship between inequality and economic growth. From this it follows that at least a slight increase in the degree of inequality is necessary in order to haul initially poor and low educated economies out of the poverty trap. However, as economies become educated, the effect of educational inequality mainly works indirectly. Accordingly, countries that show greater educational inequality experience lower macro economic returns to education than more equal economies, on average.

Keywords: education, economic growth, distribution of education.

JEL-Codes: D31, I00, O15.

1 Introduction

The broad concept of human capital comprises aspects inherent in humans, which are - as in the case of congenital abilities, skills and talent - either given or - as in the case of education, experience and health - develop over time. In this context education obtained through the formal schooling system takes on an essential role in linking those two components of human capital. Education is able to compensate for congenital differences as well as educational gaps arising in early childhood. Equal access to education therefore secures equality of opportunities. Education also constitutes the foundation of individuals' professional careers and affects, among other things, life-time income and health - thus well-being over the whole life-cycle.¹

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¹As from now we abstract from other components of human capital and use the notions of human capital and education interchangeable. Moreover, when talking about education we are always considering education obtained through the formal schooling system. Even if this seems a substantial abstraction, it is not only necessary due to data limitations but also reasonable as formal education is the component of human capital which can be affected most easily by policy.

The aggregate stock human capital is considered a key element in the determination of economic development. This is true for industrialized countries, where human capital is vital for technology driven, sustainable development and for developing countries, where education is an essential factor for hauling societies out of poverty. Therefore, neoclassical and endogenous growth theories have been attributing peculiar roles to human capital as it brings about technological progress through positive education externalities (Lucas, 1988), idea creation as a basis for innovation (Romer, 1990), or imitation and adoption (Nelson & Phelps, 1966).

The link between individual human capital and the aggregate stock of human capital is not straightforward but depends on spillovers and the distribution of human capital within an economy. If the individual returns to education are identical across people and diminishing on the margin (Galor & Moav, 2004), then a redistribution of education to the less educated would increase the average stock and productivity of human capital, thus output. But people may differ both in their inherent abilities, skills and talents as well as their capability to develop them over time. Even if returns to education are distributed unequally, more equality can lead to an improvement in the average level and the return to human capital iff the actual distribution is more unequal than the optimal distribution, where marginal returns are equalized across people.² The theoretical literature gives ample evidence for this possibility (Sauer & Zagler, 2012). In particular, López *et al.* (1998) highlight the imperfect tradability of education, causing marginal products not to be equalized across individuals and aggregate income to depend not only on the total level but also on the distribution of the respective asset. It is due to these peculiarities that, in the presence of credit market constraints and human capital indivisibility, social inheritance of education and/or education externalities, the degree of human capital inequality negatively affects the average stock of and the macro return to human capital, hence economic development.

Numerous works have aimed at finding empirical support for the theoretically predicted strong relation between human capital and economic growth. However, results from introducing various indicators of education enrollment and attainment into growth regressions turned out to be inconclusive. The failure to consistently estimate the macro economic return to education also contrasts micro econometric evidence which well establishes a positive relation between education and income at the individual level. Reasoning for this “Education Puzzle” (López *et al.*, 1998) has ranged from econometric issues and deficient quality of schooling data (e.g. Krueger & Lindhal, 2001; Cohen & Soto, 2007) to the omission of institutions (e.g. Pritchett, 2001) and the quality of education systems (e.g. Hanushek & Kim, 1995). By showing that differences in the education level of young age groups

²The full spillover and welfare enhancing effects of education are thus not reached at the aggregate level. In this spirit, Fan *et al.* (2001, 3) argue: “If people’s abilities are normally distributed, then a skewed distribution of education opportunities represents large welfare losses. (...) an equitable distribution of human capital (...) constitutes a precondition for individual productivity and ability to rise above poverty. Furthermore, an equitable distribution of opportunities is preferable to a redistribution of existing assets or incomes. This is because education builds new assets and improves social welfare by its spillover effects, without making anyone worse off. Ensuring access to educational opportunities by attending to both the supply and demand sides, is a win-win policy gaining support in industrial and developing countries.”

explain differences in income per capita significantly better than aggregate measures, Lutz *et al.* (2008) provided evidence on the importance of allowing for the demographic dimension of human capital.

Not much attention has been devoted to the distributional dimension so far. If the distribution of education actually matters but is omitted, however, a negative correlation between educational inequality and average attainment would cause the macro return to education to be consistently biased downwards.³ The contribution of this paper is to explicitly include distributional considerations in the macroeconomic estimation of educational returns, and test whether these macroeconomic returns differ for different degrees of educational inequality.

We use Barro and Lee's (2012) education data set and compute Gini coefficients of educational attainment for a panel of 143 countries ranging from 1950 to 2005 at five-year intervals. We add this distributional measure to a conventional convergence specification following the augmented Solow model. However, based on theoretical predictions and empirical facts, we claim that a specification which properly reveals the relationship between average educational attainment, its distribution and economic development should allow for a heterogeneous macro economic return to education as well as non-linearities in the effect of educational inequality. By applying the system GMM estimator to linear benchmark equations and an interactive specification, we find strong and robust evidence supporting the presumed non-linear relationship. As this approach has not been applied in empirical studies so far, it provides new insight into the mechanics and channels of the link between education, its distribution and economic development. Moreover, it adds to the extensive empirical literature that deals with computing reliable estimates of the macro return to education.

The remainder of this paper is organized as follows. Section 2 provides a survey of the theoretical literature on the relationship between economic development and the level as well as the distribution of human capital respectively. Section 3 summarizes existing empirical evidence. Thereafter, we describe our data and the methodology in sections 4 and 5. Estimation results and robustness tests are presented in sections 6 and ???. Finally, we conclude in section 7.

2 The Role of Human Capital Inequality in Economic Development

Economists have long analyzed the relationship between inequality and growth. Whereas early approaches underlined the beneficial nature of inequality for economic development, the modern perspective highlights the potential of inequality to curb economic growth.⁴ In this line of research, besides the distribution of wealth and income, the distribution of human capital is considered as forming an important aspect of the overall degree of inequality within a society. Of primary interest for the

³According to Topel (1999), if distributional aspects of human capital are relatively stable within a country, they are removed by controlling for country specific effects in a panel data framework. As will be shown in 4, this assumption does not hold for the sample period under study.

⁴For good surveys on the literature about the relationship between inequality and growth see García-Penalosa (1994), Aghion *et al.* (1999) and more recently Galor (2009).

study of the relationship between the distribution of education and economic development are partial equilibrium models explaining the respective link through the human capital accumulation channel, i.e. approaches that highlight the effect of inequality on education investment decisions and hence on an economy's income level. They are able to explain persistent differences in educational attainment and income within as well as across countries. The concerning literature can be broadly classified into four lines of research.

First, if credit markets are imperfect or fully absent, initial wealth is the only source for financing human capital accumulation and poor individuals are constrained in their education investment. Inequality in the initial distribution of wealth therefore adversely affects the division of the population between skilled and unskilled labor, i.e. the distribution of human capital, what, in turn, constitutes the prime source of a society's failure to exercise its full economic potential in the short as well as in the long run. (e.g. Galor & Zeira, 1993)

As the credit market imperfection view assumes that education is solely funded privately, it does not account for the possibility that publicly provided education might mitigate part of the adverse effect of inequality, a point considered by the political mechanism approach. In general, these works draw on voting behavior differing across heterogeneous individuals according to their endowment with wealth, income or human capital. While the majority of earlier studies in this tradition predict a negative relation between inequality and economic development due to unequal societies voting for inefficient redistributive policies⁵, more recent studies point to the welfare-increasing nature of redistributive policies. In this spirit, Glomm & Ravikumar (1992) show that even if private education is generally more productive than public education, for inequality levels sufficiently pronounced, median-voter decisions will result in a public education regime whereby inequality is reduced faster than in the private regime and average human capital is increasing for some periods. As the society becomes more equal and educated, the median voter will choose the private education regime, which allows for approaching a higher steady state income level.

Third, the main idea of a more recent strand of research is that initial differences in individuals' socio-economic background directly translate into heterogeneous education investment decisions. Based on vast empirical evidence of the importance of students' socio-economic background in determining educational outcomes, Mejía & Pierre (2008) argue that there are crucial complementary factors to the process of human capital formation⁶, that are non-purchasable in the market. Well endowed agents accumulate human capital and provide skilled labor, whereas the badly equipped choose to supply unskilled labor. Similar to previously presented models, the aggregate outcome hence depends on the relative weight of initially rich to poor dynasties. Moreover, if individual human capital

⁵See e.g. Alesina & Rodrik (1994), Persson & Tabellini (1994).

⁶Such factors that complement time and effort in the formation of human capital are race, genes, socio-economic characteristics and family background variables such as parental education, culture, provision of social connections, installation of preferences and aspiration in children as well as other factors, e.g. neighborhood and peer effects, distance to schools, and different qualities of books, teachers and schools, among other things (Mejía & Pierre (2008), 396).

is subject to decreasing returns to investment, inequality in the distribution of education impairs the average level and return to human capital. This negative relation persists and compounds in the long run through the intergenerational transmission of education within dynasties as well as amplifying relations between education and fertility choices (e.g. Moav, 2005; de la Croix & Doepke, 2003) and/or life expectancy (e.g. Castelló-Climent & Doménech, 2008).

Finally, the fourth line of research introduces human capital externalities, i.e. a mechanism through which individual education investment decisions not only affect human capital formation of future generations within dynasties but also across dynasties. Thereby these works serve to explain the simultaneous evolutionary patterns of the level and the distribution of human capital and economic development. By introducing the possibility of education costs to decrease with the average stock of human capital, extensions to the conventional credit-constraints approach (e.g. García-Penalosa, 1993) establish a positive education externality. On the one hand, in rich and high educated countries where education is relatively cheap, inequality reduces the proportion of people who can afford to study and hence impairs growth. On the other hand, in poor countries with low levels of average human capital, a temporary increase in the degree of educational inequality allows for a strong decline in education costs what enables more people to become educated and accelerates growth for some periods. In Glomm & Ravikumar (1992), on the other hand, average human capital determines the quality of public schooling. Higher average human capital therefore increases the return to education investment for skilled as well as unskilled labor by the same amount and hence accelerates average human capital accumulation as well as growth. In fact, by inducing spillovers between dynasties, the human capital externality is what makes public education favorable over private education if inequality is pronounced. The education externality might also work through the production of goods. According to Galor and Tsiddon (1997), only for inequality sufficiently low, a global technological externality which increases everybody's productivity is released. However, a slight degree of polarization in early stages of development enables to hit the threshold value of human capital which induces the beneficial technology shift.

These theoretical approaches have clear and strong empirical implications, generally predicting a negative relation between inequality in the distribution of education and economic development. The effect might differ across countries according to their initial stock and distribution of human capital. A positive relation might result from the possibility of a temporary increase in the degree of inequality to allow for jumping on a higher growth path. Not only is the distribution of human capital related to income growth through its effect on human capital accumulation but also through its relation to the aggregate return to education. That is, the more unequally education is distributed, the lower the productivity as well as the externality which emerges from education.

3 Related Empirical Literature

The relationship between the distribution of education and economic performance has been scarcely explored empirically. One line of research departs from the failure of empirical studies to support the theoretical implication of a strong causal link from education to growth. The distribution of education is considered as an omitted variable, whose inclusion should deliver more reliable estimates of the social return to education.

López *et al.* (1998) use average schooling as well as the standard deviation of educational attainment as explanatory variables in a GDP-per-capita regression. By applying fixed effects estimation to a panel of 12 Asian and Latin American countries covering the period from 1970 to 1994, they find a higher degree of inequality in the distribution of education to be significantly negatively related to GDP per capita. Controlling for distributional aspects as well as for non-linearities reveals the macro return to average schooling to be most pronounced and significant. Fan *et al.* (2001) include the education Gini index into growth regressions. By using fixed as well as random effects estimation in a panel of 85 countries ranging from 1960 to 1990, they find a significantly negative relation between the degree of inequality in the distribution of educational attainment and per capita PPP GDP increments. In a separate regression, the effect of average years of schooling on income is significantly positive. However, if both schooling variables are included in one regression equation, the return to average educational attainment remains positive and significant but the education Gini turns insignificant, indicating average human capital as an important channel linking inequality and growth.

Another line of research aims at revealing the relationship between the general concept of inequality and economic development. Castelló & Doménech (2002) compute Gini indices of human capital for 108 countries from 1960 to 2000, based on Barro and Lee's (2000) dataset on educational attainment. In order to deepen insight into the relation between inequality and economic development they use the initial level of their inequality measure in a reduced form equation with average growth in per capita income from 1960 to 1990 depending on initial income and average accumulation rates of human and physical capital. All their specifications reveal a significantly negative relationship between educational inequality and growth. Beyond that, by using physical capital accumulation as the dependent variable they show that educational inequality is also indirectly related to economic growth through the accumulation of factors. In their subsequent works (Castelló-Climent & Doménech 2008 and Castelló-Climent 2010a), the authors provide evidence for demographic channels to be the most relevant mechanisms in linking inequality, human capital accumulation and growth.

In his substantial empirical research on inequality and economic development, Castelló-Climent (2010a, 2010b) succeeds in verifying the strong negative relation between human capital inequality and income growth, observed in previous cross-section regressions, by estimating a dynamic panel data model that allows for fixed effects as well as persistent and endogenous regressors. Beyond that,

the author’s findings suggest the effect of human capital inequality to differ across countries according to the level of development. While the relationship between the education Gini coefficient and the per capita income growth rate is significantly negative in low and middle-income countries, it loses significance in higher-income countries. According to Castelló-Climent (2010b), this result can be traced back to the fact that the major channels through which inequality is predicted to negatively affect income growth (i.e. political instability, credit market imperfection, education differentials in fertility and life-expectancy) are predominantly at work in developing countries.

This work contributes to the presented empirical literature by combining two seminal papers and adding a third element. First, we continue along the lines of López *et al.* (1998) in computing reliable estimates of the macro economic return to education which account for the relevance of its distribution among the population. Second, we follow Castelló-Climent (2010a and 2010b) by controlling for unobservable individual effects, dynamic panel bias as well as endogenous and persistent explanatory variables and apply the system GMM estimator. Most importantly, however, we take the theoretical literature which predicts a nonlinear relationship between inequality and development serious. A straight forward approach for dealing with heterogeneous coefficients is the inclusion of an interaction term between the distribution and the average level of human capital.

4 The Data

We construct a panel dataset that contains information on the one hand about real GDP per capita and variables typically constituting its determinants in a neoclassical growth model, i.e. investment in physical capital and population growth, and, on the other hand, about the average level as well as the distribution of educational attainment. Data on real GDP per capita, the share of physical capital investment in real GDP and population growth are from the current release of Penn World Tables (PWT 6.3), which provides annual series for 189 countries from 1950 to 2007.⁷ (Heston *et al.*, 2009)

In order to estimate the degree of inequality in the distribution of human capital we apply the Gini coefficient as a relative measure of dispersion to the distribution of educational attainment within a concerned population. López *et al.* (1998) were the first to derive educational Gini coefficients for 12 countries based on attainment data. Fan *et al.* (2001) provide a detailed description of the underlying methodology, calculate educational Gini’s for 85 industrialized and developing countries for the period from 1960 to 1990 and relate them to average educational attainment, educational gender-gaps and real GDP per capita. They further extend their sample to 140 countries from 1960 to 2000 in their subsequent work (Fan *et al.*, 2002). Thereafter, their approach has been utilized for deriving a consistent indicator of the distribution of education ⁸, that can be related to, among other

⁷Real GDP per capita and real investment are based on 2005 constant prices. Real investment includes private as well as public investment.

⁸Fan *et al.* (2002) also calculate Theil indices of educational attainment and Castelló & Doménech (2002), Castelló-Climent (2010b) additionally report the distribution of education by quintiles.

things, the distribution of income, e.g. (e.g. Checchi, 2000), and income growth (e.g. Castelló-Climent 2010a and 2010b, Castelló & Doménech 2002 and 2008).

The concept of the Education Gini Coefficient is similar to that of the widely used income Gini, which is defined “...as the ratio to the mean of half of the average over all pairs of the absolute deviations between (all possible pairs of) people.” (Deaton 1997 in Fan et al. 2001, 7). At the macro level, we are usually restricted, however, to information on the duration of formal schooling categories and the corresponding population shares of educational attainment. All people for whom an education level is the highest attained, accomplish the same years of schooling. Formal education is hence a categorical rather than a continuous variable. It has a lower boundary at zero years of schooling, accruing to people without any formal education, and an upper boundary, given by the cumulative duration of tertiary education. We take all necessary information from the most recent release of Barro and Lee’s (2012) schooling dataset.⁹ For each country and time interval the Gini coefficient is given by,

$$G^E = \frac{N}{N-1} \frac{1}{\mu} \sum_{i=1}^6 \sum_{j=i}^5 |\tilde{s}_i - \tilde{s}_j| a_i a_j \quad (1)$$

where μ are average years of schooling of the population aged 15 and over. In accordance with Barro & Lee (2012), we consider seven categories of educational attainment¹⁰, which are identified by the indices i and j in (1). a_i and a_j are the attainment figures corresponding to each schooling level. \tilde{s}_i and \tilde{s}_j depict cumulative years of the duration of formal schooling cycles, which are calculated from Barro and Lee’s (2012) figures of average years of schooling at each level and the corresponding attainment data. Depending on country and time period under consideration, formal primary and secondary schooling cycles vary between three and nine as well as three and eleven years respectively. By contrast, all countries in the sample feature four years of formal tertiary education. For example, the education system of the United States features 6, 12 and 16 cumulative years of primary, secondary and tertiary education respectively. We assume that people who do not complete an education level to obtain half of the duration of the corresponding education cycles. Finally, the term $\frac{N}{N-1}$ adjusts the Gini coefficient for small population size. From (1) it becomes clear that the education Gini always lies in a range between 0 and 1, indicating perfect equality and perfect inequality respectively.

Through the combination of both data sources we derive an unbalanced panel consisting of 143 countries from 1950 to 2005 at five-year intervals, comprising 1383 GDP- and 1716 schooling-observations. From figure 1 it becomes evident that an overall trend of education expansion, accompanied by a reduction of inequality in the distribution of education has taken place over the period

⁹Their methodological improvements (they exploit information from UNESCO, Eurostat and OECD available at five-year age intervals, improved their estimation technique for filling in missing observations and use new calculations of mortality rates by age and education as well as estimates of completion ratios by age) as well as the extended time and individual dimension has significantly increased quality of educational attainment data. They report attainment figures ranging from 1950 to 2010 in five-year intervals for the population aged 15 and over, disaggregated by sex and age.

¹⁰(0) no schooling, (1) incomplete primary schooling, (2) complete primary schooling, (3) first cycle of secondary schooling, (4) second cycle of secondary schooling, (5) incomplete higher education, (6) complete higher education.

Table 1: Summary statistics (2005)

region	obs	Average years of schooling				Education gini			
		mean	sd	min	max	mean	sd	min	max
<i>total</i>	143	7.83	2.69	1.24	12.91	0.33	0.17	0.05	0.83
<i>Advanced Economies</i>	24	10.4	1.53	6.47	12.91	0.22	0.06	0.1	0.34
<i>Europe and Central Asia</i>	20	10.32	1.08	8.57	12.75	0.15	0.05	0.05	0.26
<i>Latin America and Caribbean</i>	25	7.95	1.56	4	10.14	0.31	0.1	0.12	0.55
<i>East Asia and the Pacific</i>	18	7.87	2.1	3.91	11.47	0.3	0.11	0.17	0.51
<i>South Asia</i>	7	5.3	2.53	3.38	10.8	0.51	0.16	0.2	0.73
<i>Middle East and North Africa</i>	18	7.34	2.11	2.96	11.28	0.4	0.14	0.21	0.73
<i>Sub-Saharan Africa</i>	31	5	2.1	1.24	9.24	0.5	0.18	0.21	0.83

under study. While the distribution of average years of schooling across the sample has been skewed to relatively low values in 1950, it is skewed towards educational achievement above ten years in 2005. The distribution is, however, quite spread out and shows a second mode below five years of schooling, indicating that huge differences across countries still persist. On the other hand, the distribution of the education Gini coefficient has narrowed and is concentrated at a relatively low value in 2005. Countries have thus been converging in terms of their educational distribution.

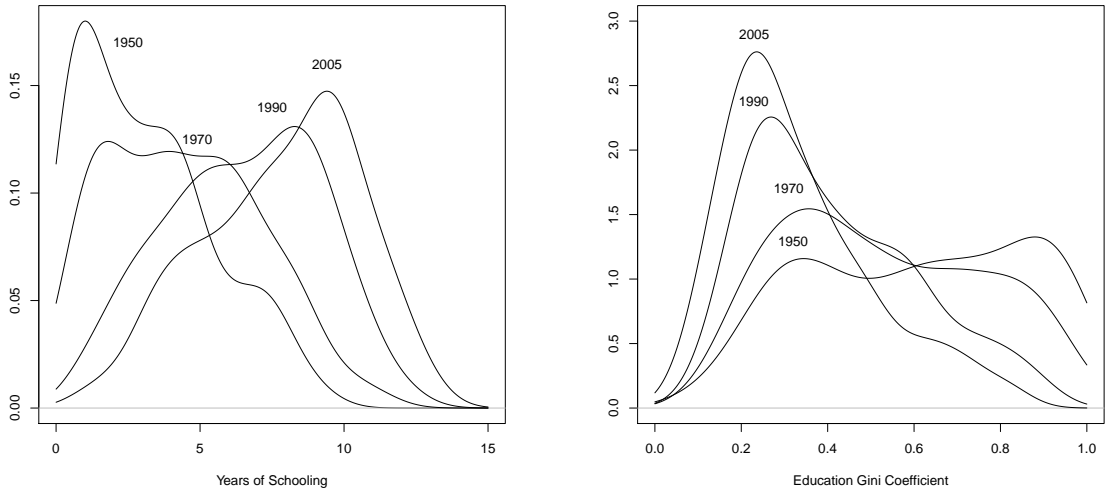


Figure 1: Kernel Density Estimates

Table 1 reports 2005 summary statistics of average years of schooling and the education Gini. Across all 143 countries in the sample educational attainment averages at 7.83 years of schooling, with the respective value for the education Gini being 0.33. The minimum and maximum values of the concerning schooling variables indicate the existence of huge differences between regions and countries, though. That is, average schooling ranges from 1.24 years in Mozambique to 12.81 in the United States. Education is most evenly distributed ($G^E = 0.05$) in the Czech Republic. By contrast, Niger reports the maximum education Gini of 0.83, accruing from an enormous illiteracy rate of 80%.

Indeed, high illiteracy rates coincide with high education Gini values. In all countries with education Ginis greater than 0.5, at least half of the population did not attain any formal education. South Asian and Sub-Saharan African countries are located at the upper left in the level-distribution plane (see figure 2). They thus report, on average, the lowest average level of schooling and the highest degree of educational inequality in 2005. On the contrary, advanced economies as well as European and Central Asian countries, exhibiting high average educational attainment in conjunction with a low degree of inequality, are located at the bottom right. The general shape of the relation between the average level of and the degree of inequality in educational attainment within the remaining regions, reporting medium values of years of schooling and the education Gini coefficient in 2005, is mainly driven by high-dynamic countries. That is, the development (see figure 3) e.g. of Iran in the Middle East, the Republic of Korea in East Asia or Brazil in Latin America was characterized by enormous educational expansion and a swift decline in educational inequality. These countries thus feature values of the concerning schooling variables which span almost the whole plane.

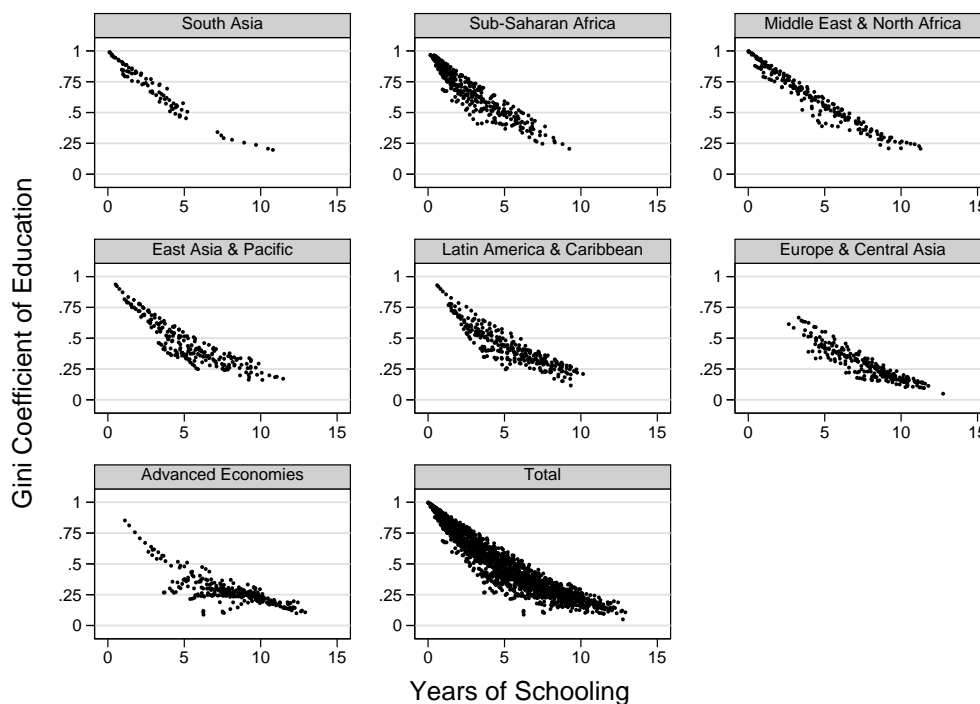


Figure 2: Average Years of Schooling vs. Education Gini Coefficient by Region

From this it follows that, even if the overall panel relation between years of schooling and the education Gini coefficient is negative, the slope changes according to the location in the level-distribution plane. While it is negative and steep below five average years of schooling, it becomes successively flatter as the degree of inequality further decreases and the average level of educational attainment increases. It therefore matters at which level of educational attainment one looks at the relation

between inequality and growth and, vice versa, at which degree of inequality one looks at the effect of years of schooling on income growth. Most importantly, however, the within variation differs across countries, even if their educational conditions have been similar at the beginning of the sample period (see e.g. Niger and Iran in figure 3). In addition, the relation between average years of schooling and the education Gini coefficient within countries over time need not to be strictly negative. As it becomes clear from figure (3), educational inequality remained constant until 1990 in the Czech Republic. Thereafter, the distribution of educational attainment has gradually become more equal, as it did the United States. On the other hand, the degree of educational inequality did not change significantly in the United Kingdom while it increased in France until 1985. Similar levels of average educational attainment therefore involve different compositions of the educational structure, reflected in varying degrees of inequality. The analysis of the growth effects of such variations in the educational Gini coefficient, holding average schooling constant, is thus what is of prime interest for our work.

5 The Method

We investigate the relationship between five year average annual income growth rates, the average level and the distribution of educational attainment respectively by adopting a conventional convergence regression,

$$[\ln(Y_{i,t}) - \ln(Y_{i,t-\tau})] / \tau = \alpha + \beta_1 \ln(S_{i,t-\tau}) + \beta_2 G_{i,t-\tau}^E + \gamma X_{i,t} + \epsilon_{i,t} \quad (2)$$

where $Y_{i,t}$ is real GDP per capita in country i in period t and $Y_{i,t-\tau}$ is the respective value of the preceding period $t - \tau$. The dependent variable is therefore the growth rate of real GDP per capita, measured as annualized averages over the respective time interval τ preceding t , i.e. five years. The two independent variables of interest, namely the level of human capital, measured as average years of schooling $S_{i,t-\tau}$, and its distribution, measured by the education Gini coefficient $G_{i,t-\tau}^E$ introduced in the previous section, are stock variables of preceding period $t - \tau$. We follow the augmented Solow model in including a set of control variables¹¹ X , containing the lagged log of real GDP, the log of the physical capital investment ratio $(I/Y)_{i,t}$ and the log of the population growth rate $n_{i,t}$. The matrix of control variables is therefore defined as

$$X_{i,t} = \{\ln(Y_{i,t-\tau}), \ln((I/Y)_{i,t}), \ln(n_{i,t})\}$$

The composite error $\epsilon_{i,t}$ consists of vector of time dummies ξ_t , a time invariant country specific effect μ_i and a remaining idiosyncratic error $\nu_{i,t}$ of country i in period t .

$$\epsilon_{i,t} = \xi_t + \eta_i + \nu_{i,t}$$

The preceding considerations have given strong indication of the relationship between the distribution of education and economic growth to be non-linear. First, the theoretical literature suggests

¹¹All control variables are measured as annualized averages over four years preceding t .

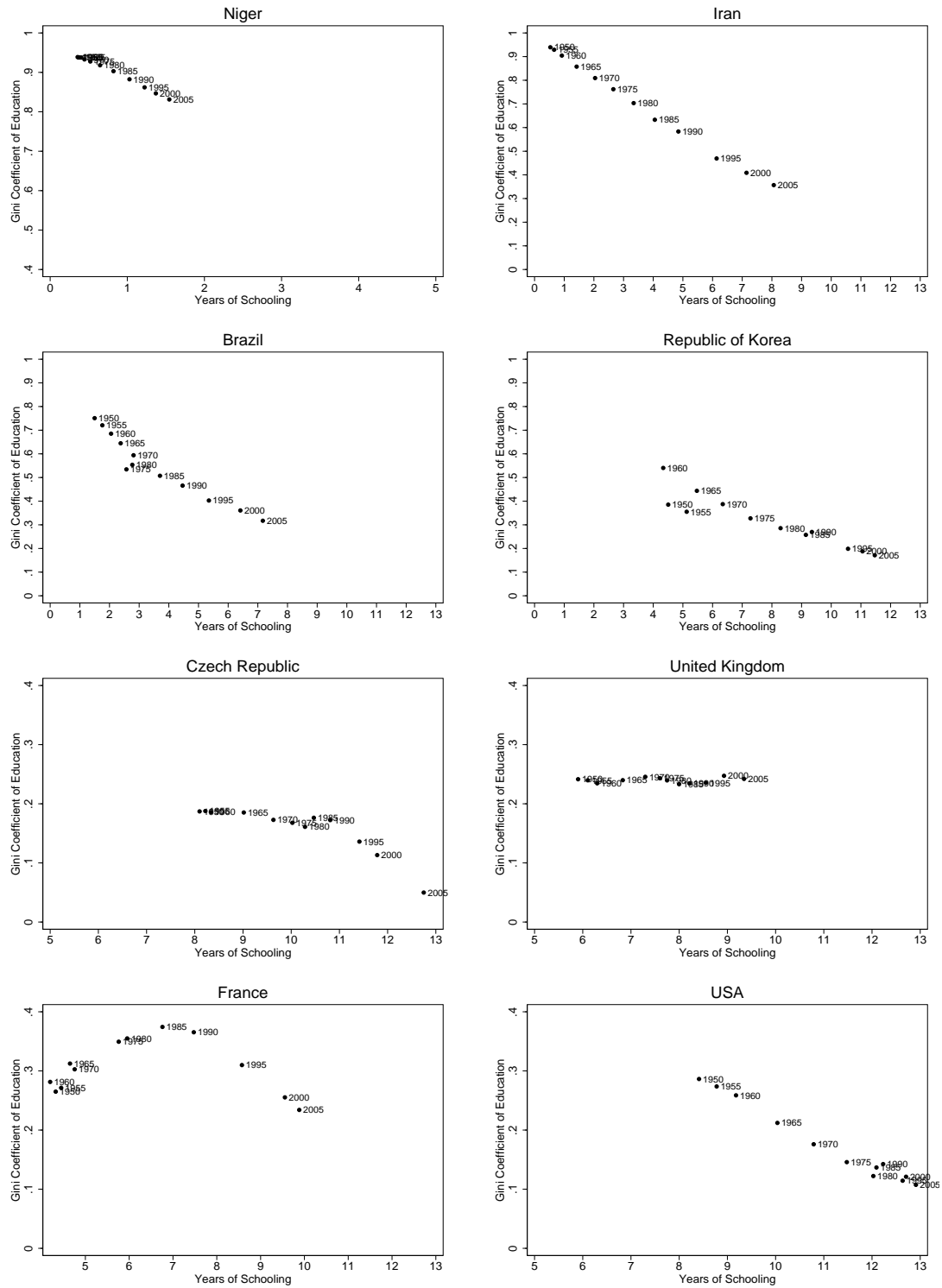


Figure 3: Average Years of Schooling vs. Education Gini Coefficient, selected countries

that poor economies may benefit from a transitional increase in educational inequality, whereas rich economies *ceteris paribus* may see faster economic growth with a more equal distribution of educa-

tion. Moreover, the aggregate productivity of education and spillover effects, i.e. the macro return to education, are predicted to be higher in more equal societies. Second, we have to distinguish a mechanical from a behavioral relationship. That is, high and low average educational attainment is associated with low and high values of the education Gini coefficient by construction. In between these extremes, however, we find within-country developments to be heterogenous. The empirical fact of a changing slope in the relation between years of schooling and the education Gini necessitates to control for the average level and the distribution of education when estimating the associated growth effects. We therefore introduce an interactive specification with a multiplicative (interaction) term between average years of schooling and the education Gini coefficient,

$$[\ln(Y_{i,t}) - \ln(Y_{i,t-\tau})] / \tau = \alpha + \beta_1 \ln(S_{i,t-\tau}) + \beta_2 G_{i,t-\tau}^E + \delta I_{i,t-\tau} + \gamma X_{i,t} + \epsilon_{i,t} \quad (3)$$

with

$$I_{i,t-\tau} = \ln(S_{i,t-\tau}) * G_{i,t-\tau}^E \quad (4)$$

The basic specification (2) describes a general relationship between real GDP per capita and the two schooling variables, i.e. the coefficient on average years of schooling β_1 estimates the elasticity of the growth rate of real GDP per capita with respect to $S_{i,t}$ across all levels of $G_{i,t-\tau}^E$. Vice versa, β_2 estimates the change in GDP growth associated with a one-unit change in $G_{i,t-\tau}^E$ across all levels of $S_{i,t-\tau}$. By contrast, non linear models allow for estimating conditional relationships, i.e. the average effect of $S_{i,t-\tau}$ and $G_{i,t-\tau}^E$ on GDP growth, conditional on particular levels of $S_{i,t-\tau}$ and $G_{i,t-\tau}^E$ respectively. The coefficient β_1 in (3) hence estimates the percentage change in GDP growth associated with a one-percentage change in $S_{i,t-\tau}$ when $G_{i,t-\tau}^E$ is equal to zero, with the reverse being true for β_2 . The coefficient on the multiplicative term δ measures either the change in β_1 associated with a one-unit change in the distribution of education or the change in β_2 associated with a one-unit change in logged average years of schooling.

In both specifications (2) and (3) we are estimating a dynamic model in real GDP per capita, which allows for country-specific characteristics. Therefore, an appropriate estimation technique should be able not only to deal with unobservable individual effects but also with the dynamic panel bias. That is, the lagged dependent variable is necessarily correlated with the country-specific intercept as well as with the time-varying error. The crucial assumption of strict exogeneity, which requires the idiosyncratic error to be uncorrelated with all explanatory variables at all time intervals, is thus always violated in this dynamic framework. Moreover, the issue of endogeneity also arises with respect to the explanatory variables of our interest. For example, it is reasonable to assume the average level and the distribution of human capital to be determined simultaneously with income. In addition, by having more means for investing in education in general as well as for providing high quality public education, rich economies will not only accumulate a higher stock of human capital but also achieve a more equitable distribution of educational attainment than poor economies. This issue of reverse causality

has already been subject to discussion on theoretical as well as empirical grounds (e.g. Bils & Klenow (2000)). In order to cope with these estimation problems we use the instrumental variable approach of the system General Method of Moments (GMM), as has initially been proposed by Arellano & Bover (1995) and Blundell & Bond (1998). The basic idea of this method, designed for dynamic panels with a small time and relatively large individual dimension, is to estimate a stacked system of equations in first differences and in levels simultaneously. On the one hand, differencing eliminates unobservable individual effects. The identifying assumption of lagged levels being orthogonal to the time-varying error enables us to use them as internal instruments for predetermined or endogenous regressors. On the other hand, the identifying assumption of lagged first differences being orthogonal to the time-invariant error component makes them valid instruments in the levels equation. We assume initial GDP per capita to be predetermined so that $Y_{i,t-2\tau}$ (and deeper lags) and $\Delta Y_{i,t-\tau}$ are available as instruments in the equation in first differences and the levels equation respectively. By contrast, treating average years of schooling, the Gini coefficient of education and population growth endogenous necessitates to go one further period back in order to obtain valid instruments.

Consistency of system GMM crucially hinges on identifying assumptions securing the validity of instruments, i.e. exogeneity of lagged levels and lagged differences in the first difference and the levels equation respectively as well as serially uncorrelated idiosyncratic errors. In particular the assumption needed for instruments added by the levels equation to be valid is not trivial, since it requires stationarity of explanatory variables. Yet Roodman (2006) demonstrates this requirement to hold if initial deviations from a series' steady state are uncorrelated with the fixed effect, which is likely to be the case if a series' starting point lies far behind the analyzed sample period. If so, stationarity would be assured even without transforming data into deviations from period means by adding time dummies, as in (2) and (3). Evaluating if identifying assumptions hold is essential, though. We therefore report three specification tests. First, the Hansen test of over identifying restrictions tests the null hypothesis of joint validity of the whole instrument set. Second, the difference-in-Hansen test tests for the validity of moment conditions added by appending the set of levels equations. Finally, the third test we perform is the Arellano-Bond test for autocorrelation, which aims to detect first-order serial correlation in levels through testing for second-order serial correlation in the residuals in differences.

The system GMM estimator generates instruments quadratic in the time dimension (T). The instrument count can hence easily grow large relative to the sample size as T rises, and may induce severe finite-sample problems. Typical for all instrumental variable techniques, too many instruments can overfit endogenous variables, failing to expunge their endogenous components and biasing coefficient estimates (Roodman, 2007). Moreover, the Hansen as well as the difference-in-Hansen test of instrument validity become weak as instruments become numerous. In order to secure reliability of estimation results, we therefore limit the instrument set to the first available lag of predetermined and

endogenous variables respectively.

6 Results

We estimate equations (2) and (3) in a dynamic panel over 60 years and 143 countries with a system GMM estimator in order to explore the relationship between economic development, average educational attainment and the degree of educational inequality. Whereas specification (2) follows the conventional literature, we introduce an interaction term in specification (3). This allows for heterogeneity in the effects of schooling and its distribution on economic growth along the average level and the distribution of education, respectively.

Table 2: Regression results

	$[\ln(Y_{i,t}) - \ln(Y_{i,t-\tau})] / \tau$			
	(1)	(2)	(3)	(4)
$\ln(Y_{i,t-\tau})$	-0.014 (2.656)***	-0.018 (3.287)***	-0.011 (2.121)**	-0.020 (3.139)***
$\ln(I/Y)_{i,t}$	0.022 (2.778)***	0.025 (3.284)***	0.019 (2.911)***	0.022 (3.724)***
$\ln(n_{i,t})$	-0.010 (2.464)**	-0.006 (1.659)*	-0.003 (0.927)	0.004 (1.010)
$\ln(S_{i,t-\tau})$	0.004 (0.634)		0.000 (0.042)	0.105 (2.394)**
$G_{i,t-\tau}$		-0.046 (1.381)	-0.031 (0.765)	0.207 (2.146)**
$\ln(S_{i,t-\tau}) * G_{i,t-\tau}$				-0.091 (2.459)**
<i>constant</i>	0.028 (0.902)	0.096 (1.845)*	0.058 (1.027)	-0.071 (1.077)
<i>Observations</i>	1,182	1,182	1,182	1,182
<i>Instruments</i>	85	85	103	121
$p(AR2)$	0.843	0.846	0.882	0.887
$p(J)$	0.089	0.203	0.109	0.454
$p(diff-in-J)$	0.291	0.614	0.429	0.975

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: T statistics in parenthesis. Time dummies are included for each 5-year time interval of the sample period from 1950 to 2005. Instruments are the level and the first difference of GDP per capita lagged one period as well as the level and the first difference of $\ln(I/Y)_{i,t}$, $\ln(n_{i,t})$, $\ln(S_{i,t})$ and $G_{i,t}$ lagged two periods in the first difference and the levels equation respectively. The instrument set is restricted to the first lag available. $p(AR2)$ reports the p-value corresponding to the null of no second order serial correlation in first differences. $p(J)$ and $p(diff-in-J)$ are the p-values corresponding to the Hansen test for joint validity of instruments and validity of system GMM instruments respectively.

Table 2 summarizes our regression results. We present four specifications. The first specification reported in column (1) reproduces the conventional growth regression of the augmented Solow model. The second column substitutes the log of schooling with the Gini coefficient of educational inequality.

In the third column, we include both the log of schooling to approximate average human capital, and its distribution. Finally, in the fourth column, we adopt the methodology presented in equation (3) and add an interaction term between average years of schooling and the education Gini.

In all specifications the coefficient on initial GDP per capita has the expected negative sign, is of substantial magnitude and significant. Hence conditional convergence is confirmed to be relevant for the economies building in our sample. Accordingly, countries with higher initial income exhibit lower growth rates, with the corresponding elasticity ranging from -0.011 to -0.02. In accordance with theoretical predictions, an increase in population growth curbs economic development. However we can reject the null hypothesis of no effect of population growth at the 5% significance level only in the first specification. Investment ratios prove to be significant and exhibit a positive coefficient throughout all specifications.

When estimating the macro return to education without allowing for distributional aspects we find the positive effect of average schooling to be insignificant. This confirms results found in the empirical literature, which note little to no effect of human capital on economic growth. Similarly, even if the education Gini has the expected negative sign, we do not find a significant impact if average schooling is not controlled for. Third, including the average level together with the distribution of educational attainment linearly does not reveal significant effects of the schooling variables either.

Finally, in column (4) of table 2, we introduce the proposed interaction term, thereby testing for the effect of average schooling to depend on the existing degree of educational inequality and, vice versa, for heterogeneity in the effect of inequality with respect to the existing level of educational attainment. Allowing for non-linearities turns out to be crucial as the macroeconomic return to education increases and turns significant. Moreover, coefficients on the education Gini as well as the multiplicative term are of substantial magnitude and significant. Both coefficients for average schooling and the educational Gini are positive, whereas the interaction term is negative. Of particular interest are therefore the conditional estimates, which we derive from the interactive specification (3) as follows:

$$\delta_S = \beta_1 + \delta G_{i,t-\tau}^E \quad (5)$$

$$\delta_G = \beta_2 + \delta \ln(S_{i,t-\tau}) \quad (6)$$

In order to test for the significance of conditional estimates, we compute conditional t-statistics based on conditional standard errors which measure the variability of their associated coefficients at particular levels of the respective variable (Friedrich, 1982). Results for the macroeconomic return to education conditional on the degree of educational inequality (δ_S) are presented in figure 4, which includes both conditional estimates as well as the 5% confidence interval. Accordingly, a one percent increase in average schooling boosts annual income growth by 0.105% if education is distributed perfectly equal, i.e. $G_{i,t-\tau}^E = 0$. However, with each increase of the education Gini coefficient by one standard deviation, equal to 0.235, this positive effect is reduced by 0.021 percentage points. Thus, at

the sample mean, where $G_{i,t-\tau}^E = 0.481$, we find that a one-percent increase in average schooling fosters growth by not more than 0.061% anymore. The effect diminishes substantially from an elasticity of 0.1 at the sample minimum ($G_{i,t-\tau}^E = 0.05$) to 0.001 at the sample maximum ($G_{i,t-\tau}^E = 0.998$) of the education Gini. With a high degree of educational inequality ($G_{i,t-\tau}^E > 0.75$), we can no longer reject the null hypothesis of no influence of human capital on economic growth, though.

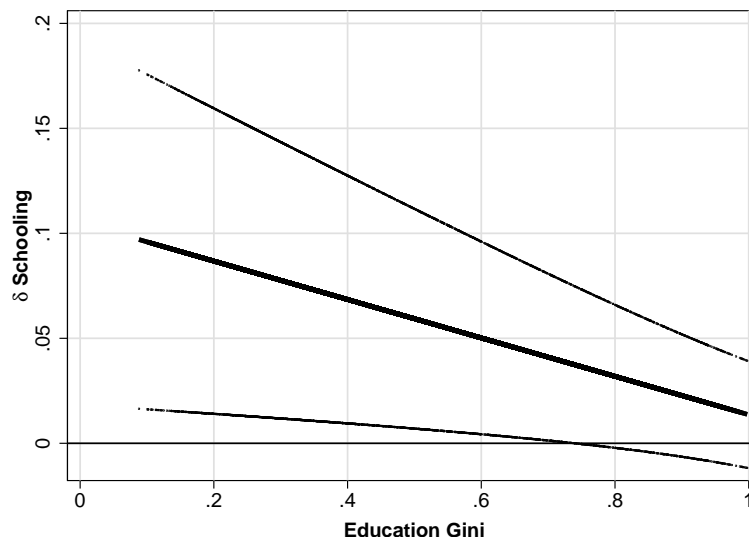


Figure 4: Conditional Estimates: δ_S

This result demonstrates that education indeed matters for economic growth, thus presenting a solution to the education puzzle. However, education matters if and only if it is not distributed unequally. Below a Gini coefficient of 0.75, an increase in education no longer has a beneficial impact on economic growth, as education will then only benefit a small elite. The impact of education is stronger the more equal education is distributed in an economy, thus redistributing education has a merit if it goes along with an overall increase in the level of education.

Figure 5, on the other hand, gives the conditional estimates of increasing educational inequality for given levels of schooling. We find that for low levels of education, an increase in inequality can promote economic growth. At the sample minimum of 0.011 years of schooling, a one standard deviation deterioration of the Gini coefficient would foster annual economic growth by 0.048 percentage points. In line with theoretical predictions, it therefore may be attractive to transitionally reallocate educational resources to more promising students for countries with very low levels of education, so they can surpass certain educational thresholds and assist in promoting economic growth in their country.¹² We also find that merely redistributing education exhibits no significant effect on economic

¹²Our result contrasts previous evidence from Castelló-Climent (2010a, 2010b), who finds income growth to be negatively related to educational inequality in low and middle income countries but insignificant in high income countries. A possible reason for this disparity is that allowing the effect of inequality to depend on the level of educational attainment enables to account for differences between countries, even within defined income groups. However, although the positive relation is supported theoretically, it might be either driven by outliers or by the omission of the demographic

growth, at least for the range above 3 years and below the sample maximum of 12.81 years of schooling. The conditional estimate turns negative but remains insignificant above 9 years of education, indicating that for very high average levels of education (beyond our sample), redistribution of education may actually lead to an increase in economic growth.

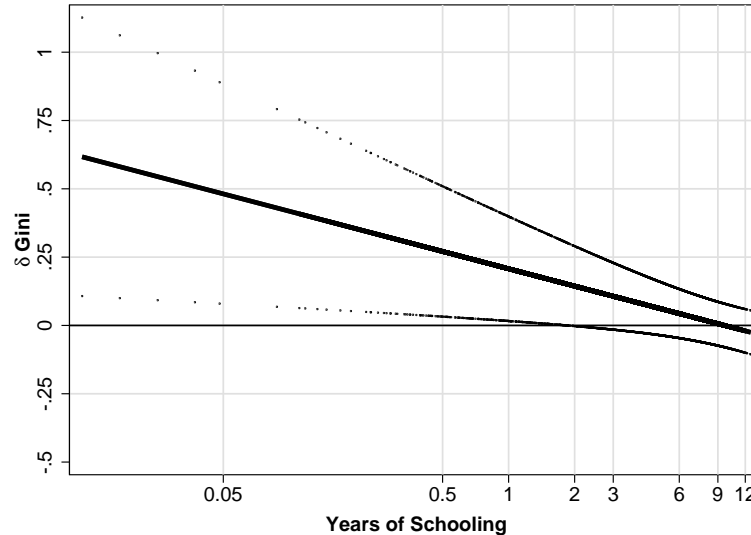


Figure 5: Conditional Estimates: δ_G

The middle panel of table 2 reports specification tests peculiar to the system GMM estimator. Limiting the instrument set to the first available lag of predetermined and endogenous variables respectively enables us to ensure that the number of instruments falls below the number of observations in each regression. Moreover, the Hansen and the difference-in-Hansen test statistic reveal overall instruments as well as instruments added through the levels equation to be valid in each specification. Finally, p-values of the Arellano-Bond test allow for accepting the H_0 of no second-order serial correlation in first differences.¹³

Theoretical approaches to the relation between human capital inequality and economic growth predict the initial degree of inequality to negatively affect average human capital accumulation, thus the aggregate level human capital and income growth, respectively. This implies the degree of ed-

dimension of inequality. That is, fast educational expansion is associated with a swift increase in educational attainment of the youth, while attainment of the elderly usually remains constant. The associated unequal distribution between age cohorts, reflected in higher education Gini values, thus imply a positive growth effect. A consistent analysis of educational inequality within and across age groups would therefore be an important aspect for further research.

¹³We have also analyzed the effects of forgoing the restriction of the instrument set. Using the first as well as all deeper lags available in the difference equation boosts the instrument count up to 292 and 346 in the linear and non-linear specification respectively. This distorts estimation considerably since, in general, all schooling variables of interest are not significant. Most importantly, testing for the validity of instruments consistently delivers implausibly high p-values of 1, what indicates weakness of the Hansen as well as the difference-in-Hansen test. The instrument count and specification tests are still not satisfactory if we limit the instrument set of endogenous variables but allow for deeper lags of the predetermined variable. However, estimation results converge to those obtained by using the fully limited instrument set as coefficients on the relevant variables are of quite similar magnitude and marginally statistically significant. The fact that results improve as the instrument count is being reduced strengthens the robustness of our preferred estimation outcomes.

Table 3: Robustness tests

	$[\ln(Y_{i,t}) - \ln(Y_{i,t-\tau})] / \tau$										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\ln(Y_{i,t-\tau})$	-0.015 (2.793)***	-0.012 (2.635)***	-0.022 (3.445)***	-0.008 (1.611)	-0.013 (2.596)**	-0.008 (1.500)	-0.016 (2.819)***	-0.009 (1.327)	-0.012 (1.749)*	-0.005 (0.916)	-0.016 (2.089)**
$\ln(I/Y)_{i,t}$	0.025 (2.769)***	0.020 (3.055)***	0.021 (4.074)***	0.031 (3.410)***	0.025 (3.098)***	0.025 (3.055)***	0.028 (3.841)***				
$\ln(n_{i,t})$	-0.005 (1.450)	-0.004 (1.465)	0.004 (0.816)					-0.009 (1.894)*	-0.003 (0.805)	-0.005 (1.616)	0.000 (0.091)
$\ln(S_{i,t-\tau})$		0.006 (0.763)	0.122 (2.877)***	-0.000 (0.029)		-0.007 (0.587)	0.062 (2.231)**	0.013 (1.838)*		0.012 (1.202)	0.149 (2.592)**
$G_{i,t-\tau}$	-0.036 (1.305)	-0.013 (0.408)	0.231 (2.645)***		-0.047 (1.848)*	-0.041 (1.068)	0.126 (1.750)*		-0.105 (2.729)***	-0.004 (0.110)	0.307 (2.396)**
$\ln(S_{i,t-\tau}) * G_{i,t-\tau}$			-0.107 (2.815)***				-0.057 (2.832)***				-0.109 (2.282)**
<i>constant</i>	0.071 (1.425)	0.047 (0.890)	-0.082 (1.314)	0.006 (0.219)	0.081 (1.779)*	0.049 (0.904)	-0.047 (0.670)	0.032 (0.837)	0.150 (2.190)**	0.022 (0.363)	-0.158 (1.799)*
<i>Observations</i>	1,132	1,132	1,132	1,239	1,239	1,239	1,239	1,183	1,183	1,183	1,183
<i>Instruments</i>	81	99	115	67	67	85	103	67	67	85	103
<i>p(AR2)</i>	0.908	0.931	0.967	0.744	0.729	0.703	0.745	0.901	0.906	0.913	0.955
<i>p(J)</i>	0.128	0.148	0.504	0.021	0.072	0.040	0.091	0.042	0.049	0.037	0.095
<i>p(diff-in-J)</i>	0.444	0.544	0.976	0.297	0.409	0.174	0.938	0.177	0.143	0.243	0.562

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: T statistics in parenthesis. Time dummies are included for each 5-year time interval of the sample period from 1950 to 2005. Instruments are the level and the first difference of GDP per capita lagged one period as well as the level and the first difference of $\ln(I/Y)_{i,t}$, $\ln(n_{i,t})$ and $G_{i,t}$ lagged two periods in the first difference and the levels equation respectively. The instrument set is restricted to the first lag available.

p(AR2) reports the p-value corresponding to the null of no second order serial correlation in first differences. p(J) and p(diff-in-J) are the p-values corresponding to the Hansen test for joint validity of instruments and validity of system GMM instruments respectively.

educational inequality to impact growth with a substantial time lag rather than simultaneously with average educational attainment, as it is implied by specifications (2) and (3). We thus allow for the education Gini coefficient one lag further behind, i.e. $G_{i,t-2\tau}^E$. The results from rerunning our regressions accordingly, are presented in columns (1) to (3) of table 3. As before, our evidence strongly indicates non-linearities in the relationship between years of schooling, the education Gini and economic growth. Indeed, the coefficients on the concerning schooling variables are not only higher in magnitude, compared to column (4) of table 2, but also significant at the one percent significance level. This provides support for the presumed lagged channel linking human capital inequality and economic growth.

In order to further assure the robustness of our results we successively eliminate control variables from the regressions (see columns (4) to (11) of table 3). On the one hand, spurious regression indicates that educational inequality might also be indirectly related to growth through a boosting effect on fertility rates, thus population growth. This is in line with theoretical works building on differential fertility choices between the well and the low educated for explaining the relationship between educational inequality and growth. The education Gini might also pick up information of population growth, as countries with an unequal distribution tend to be countries that have high population growth rates, on average. However, even if the education Gini coefficient becomes slightly significant at the 10% level in column (5) and the coefficients of schooling variables decrease in magnitude in the interactive specification, our prime results do not change substantially. On the other hand, Castelló & Doménech (2002) have noted that educational inequality could also be indirectly related to income growth through the accumulation of factors. In fact, educational inequality is significant and negatively related to income growth if neither the physical capital investment share nor average schooling are allowed for. In this case, a one standard deviation increase in the education Gini coefficient reduces annual growth by 0.025 %. Moreover, the magnitude of the estimated variable effects of schooling and its distribution are higher in column (8) than in column (4) of table 2. Due to the presumed negative relation between inequality and educational attainment as well as physical capital investment, it is most likely that these estimates are substantially biased upwards, though. In general, we therefore find that our main result which strongly supports the accountance for non-linearities hold, even in presence of spurious regression.

7 Summary and Conclusions

This paper had two main objectives. First, we aimed at demonstrating that education matters for economic growth. Despite seeming obvious, the empirical literature has so far failed to provide sound evidence. Second, we sought to find evidence on the relevance of the distribution of education for economic development. Theoretical approaches to economic growth which account for distributional aspects generally predict the degree of human capital inequality to negatively affect income growth

through the channel of human capital accumulation. But theory also provides indication not only for the effect to differ across countries according to the average level of human capital but also for the macroeconomic return to education to vary with the degree of educational inequality. Our central hypothesis has therefore been that a specification which properly reveals the relationship between average educational attainment, its distribution and economic development should allow for a heterogeneous macroeconomic return to education as well as non-linearities in the effect of educational inequality.

By adding the education Gini coefficient and average years of schooling to a conventional convergence specification and applying the system GMM estimator to linear benchmark equations, we found results to be satisfactory with respect to lagged income, investment shares and population growth, but saw little to no evidence for the impact of schooling and its distribution on economic growth. The introduction of an interaction term between the education Gini coefficient and years of schooling has turned out to be crucial in understanding the relevance of educational inequality for economic development. Doing so reveals, first, that the coefficient on average schooling increases and becomes significant as the appropriate functional form is being estimated. The failure to allow for distributional aspects and to recognize the flexible coefficient may be the reason for unsatisfactory results in previous studies. Education exhibits a positive impact that is substantially declining in the inequality of education. Accordingly, countries that show greater educational inequality experience lower macroeconomic returns to education than more equal economies, on average. Second, we find the relation between educational inequality and income growth to be positive for relatively low educational attainment. Thus, in accordance with the theoretical literature, at least a slight degree of inequality is necessary in order to haul an economy out of a poverty trap. The effect becomes, however, insignificant as economies become more educated. The conditional relationship between average educational attainment and income growth uncovers that instead of being directly related to growth, educational inequality negatively affects economic growth indirectly through its dampening effect on the macroeconomic return to education. From this it follows that the existence of constraints to the equalization of marginal individual returns to education inhibits the aggregate productivity of human capital. Moreover, inequality in the distribution of education constitutes a border to education expansion and the associated externalities, as they emerge e.g. from the quality and cost of schooling or from technological spillover effects.

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